AN RFI DETECTION ALGORITHM FOR MICROWAVE RADIOMETERS USING SPARSE COMPONENT ANALYSIS

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ABSTRACT

Radio Frequency Interference (RFI) is a threat to passive microwave measurements and if undetected, can corrupt science retrievals. The sparse component analysis (SCA) for blind source separation has been investigated to detect RFI in microwave radiometer data. Various techniques using SCA have been simulated to determine detection performance with continuous wave (CW) RFI.

Index Terms— radio frequency interference, microwave radiometry, sparse component analysis

1. INTRODUCTION

1.1. Background

Microwave radiometers use allocated spectrum dedicated to sensing the environment. As wireless communications and other active services flourish, allocated spectrum has been contaminated by illegal transmitters within the spectrum allocation or by out of band emissions from transmitters operating in adjacent bands. In some cases radiometer bandwidth exceeds the allocated spectrum to reduce measurement uncertainty or spectrum allocations are shared, forcing microwave radiometers to co-exist with terrestrial sources. If RFI is left undetected, science retrievals can be inaccurate. Low level RFI is particularly detrimental as it can be concealed as natural variability leading to flawed scientific results. As a result, RFI detection algorithms have been developed to address the problem. Research into other algorithms is needed to improve upon the sensitivity of existing detection algorithms to various types of RFI.

The sparse component analysis has been investigated to determine its sensitivity to continuous wave (CW) RFI. SCA is a blind source separation method which seeks to extract *N* unknown sources from *P* observations with weak assumptions about the sources.

1.2. Signal Model

To analyze the performance of the RFI detection model, a signal model is developed under two different hypotheses. It is assumed that the radiometer digital receiver is capable of receiving both vertical as well as horizontal polarizations, providing two observed signals. The null hypothesis, $\mathcal{H}_0$, is the case where there is no RFI present. In the null case the horizontal and vertical polarizations each contain observations of the geophysical thermal radiation modeled as two independent zero-mean Gaussian processes: $\boldsymbol{n}_H = \mathcal{N}(0, \sigma_{nH}^2)$ and $\boldsymbol{n}_V = \mathcal{N}(0, \sigma_{nV}^2)$.

Under the alternate hypothesis, $\mathcal{H}_1$, the measurement is considered to be contaminated with an RFI signal, $\boldsymbol{r}$. This gives a total of three source signals: $s_1 = \boldsymbol{n}_H$, $s_2 = \boldsymbol{n}_V$, and $s_3 = \boldsymbol{r}$. The observed signal, $\boldsymbol{x} = (x_H, x_V)^T$, can be written as a linear combination of the three sources $\boldsymbol{s}(\boldsymbol{t}) = (s_1(t), s_2(t), s_3(t))^T$. As a function of time, the system can be written as equation 1.

$$\boldsymbol{x}(t) = \boldsymbol{A}\boldsymbol{s}(t), \quad t = 1, \dots, T \tag{1}$$

$\boldsymbol{A}$ is the desired unknown mixing matrix. At each time sample, the linear system can be written as equation 2.

$$\begin{pmatrix} x_H \\ x_V \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{pmatrix} \begin{pmatrix} n_H \\ n_V \\ r \end{pmatrix} \tag{2}$$

Since $\boldsymbol{A}$ and $\boldsymbol{s}(t)$ are unknown, equation 1 defines a blind source separation problem (BSS) which is underdetermined since the number of observations is less than the number of unknown sources. The null and alternate hypotheses can be written as equations 3 and 4 respectively.

$$\mathcal{H}_0 : \begin{cases} x_H = a_{11} n_H + a_{12} n_V \\ x_V = a_{21} n_H + a_{22} n_V \end{cases} \tag{3}$$

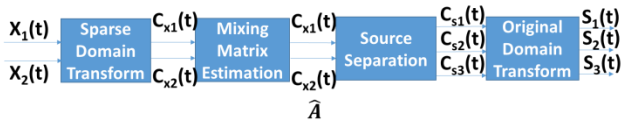

Figure 1: SCA method for extracting sources from observations.

$$\mathcal{H}_1: \begin{cases} x_H = a_{11}n_H + a_{12}n_V + a_{13}r \\ x_V = a_{21}n_H + a_{22}n_V + a_{23}r \end{cases} \tag{4}$$

Under the null hypothesis, the coefficients a_{13} and a_{23} of the mixing matrix $\boldsymbol{A}$ are set to zero such that there is no RFI contribution to the observed signal. Under the alternate hypothesis, RFI is observed and the interference to noise ratio (INR) is used to represent the level of interference. From equation 4, $INR_H = a_{13}^2/a_{11}^2$ and $INR_V = a_{23}^2/a_{22}^2$. By letting $a_{11} = 1$, $a_{13} = \sqrt{INR_H}$ and $a_{23} = \left(a_{22}\sqrt{INR_V}\right)$.

2. SPARSE COMPONENT ANALYSIS

Sparse component analysis (SCA) is a method for solving blind source separation problems for underdetermined systems. The underlying assumption of SCA is that the sources are disjoint.

3. METHODOLOGY

Based on the SCA assumption, sources need to be disjoint with only one or none of the sources being active at a given time. In practice the source signals are not disjoint in time. In order to satisfy the SCA assumption each source is transformed to a sparse representation in another domain. After a sparse domain transformation is applied to the observed signals, the mixing matrix $\boldsymbol{A}$ is estimated using the sparse coefficients obtained in the transformation. The sources are then separated in the transformed domain using the coefficients of observations and the estimated mixing matrix $\boldsymbol{A}$. The sources are finally reconstructed in the time domain. The steps of SCA are shown in Figure 1.

3.1. Sparse Domain Transform

The first step in sparse representation is to choose a set of elementary signals, known as atoms, which would be used to represent a source in the new domain. These atoms can be encompassed in a matrix, called a dictionary. To create a dictionary, dictionary learning algorithms can be applied or a structured dictionary can be created. Dictionary learning algorithms, such as K-SVD, use training signals and adapt the dictionary to training signals. Although dictionary learning provides the best representation, a very large set of training signals is required for the application where two of the source signals are noise. This makes dictionary learning computationally intensive [1], [2]. As a result, a structured dictionary is considered. This type of dictionary is based on mathematical models and consists of pre-determined atoms such as delta, sine, wavelets and wavelet packets.

Once the dictionary is determined, the signal representation can be determined in the transformed domain using either a global optimization technique (sparse coding) or greedy algorithms (matching pursuit) [3], [4]. Let K, denote the number of atoms in the dictionary, $\boldsymbol{\Phi}$. If the signal in time domain is $\boldsymbol{x}$ and the signal coefficients in the transformed domain is $\boldsymbol{c_x}$, then

$$\boldsymbol{x} = \boldsymbol{\Phi c_x} \tag{5}$$

where $\boldsymbol{x} = [x(1), \dots, x(t)]^T$ and $\boldsymbol{c_x} = [c_x(1), \dots, c_x(K)]^T$.

For sparse coding, $\boldsymbol{c_x}$ can be obtained by solving equation 6.

$$\boldsymbol{c_x} = \arg \min_{\boldsymbol{x}=\boldsymbol{\Phi c_x}} \|\boldsymbol{c_x}\|_1 \tag{6}$$

Sparse coding global optimization produces higher sparsity results compared to matching pursuit. However global optimization is more computationally intensive.

3.3 Mixing Matrix Estimation

The mixing matrix $\boldsymbol{A}$ is estimated through the scatter plot of the coefficients $\boldsymbol{c_x}$. A global clustering algorithm, weighted histogram, is used to estimate the directions of the columns of the mixing matrix. The weighted histogram method gives more importance to points with large amplitudes when determining the directions [5].

3.4 Source Separation and Signal Reconstruction

Binary masking is used to separate the sources. A mask is derived by setting the indices of the sources which correspond to the highest amplitude in observations given the mixing matrix with a value of one. Since the signals are disjoint, only the active sources are assigned a coefficient value, while the other sources are masked with zeroes [5], [6]. In the last step, the acquired source signals can be reconstructed back to their original domain by using equation 5.

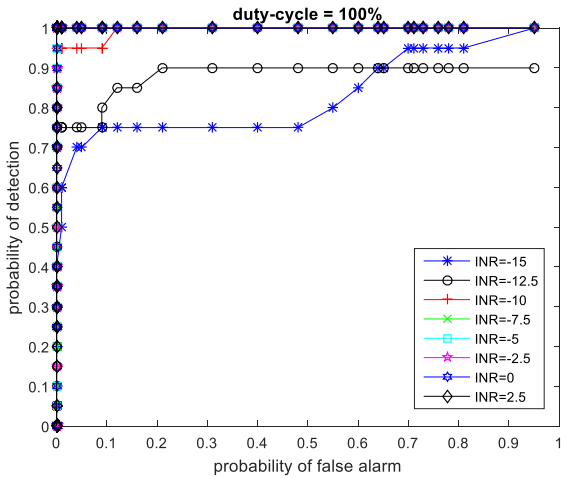

Figure 2: Receiver operating characteristic curve showing SCA detection performance for CW RFI.

3.6 Detection

The detection criterion is the median of the absolute value of the reconstructed sources, $\hat{x}$ in time. The output of SCA are three reconstructed sources in time, $\hat{s_1}(t), \hat{s_2}(t), \hat{s_3}(t)$ where t = 1, 2, 3 … N. The median of the absolute value of each reconstructed source $(median(|\hat{s_n}(t)|), n = 1, 2, 3)$ is evaluated. If all medians are greater than a given threshold, RFI is present.

4. SIMULATION RESULTS

Monte Carlo simulations with 1000 time samples are used, along with the structured dictionary and Orthogonal matching pursuit (OMP) algorithm for joint sparse representation, the weighted histogram for matrix estimation and binary masking for source separation.

Figure 2 shows the performance results of SCA for detection of CW RFI with INR_H ranging from -15 dB to 2.5 dB. The results show perfect to near perfect detection for INRs greater than -12.5 dB and very good detection at -12.5 dB and -15 dB. Results show that detection works for relatively large INRs for CW RFI.

6. REFERENCES

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